Ecological Indicators 150 (2023) 110214

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

A comparative study of green growth efficiency in Yangtze River Economic Belt and Yellow River Basin between 2010 and 2020

Liang Liu [1], Yirui Yang [1], Shu Liu, Xiujuan Gong, Yuting Zhao, Ruifeng Jin, Hongyu Duan, Pan Jiang [*]

School of Economics and Management, Southwest University of Science and Technology, Mianyang 621010, China

ARTICLE INFO

Keywords:
Green growth efficiency
three-stage DEA
Yangtze River Economic Belt
Yellow River Basin

ABSTRACT

The Yangtze River Economic Belt and the Yellow River Basin are important economic regions and ecological barriers in China. Promoting the development of the Yangtze River Economic Belt and promoting ecological protection and high-quality development in the Yellow River Basin are major regional strategies implemented by the Chinese government, and the green growth of the two regions is important for the high-quality sustainable development of the whole China. To investigate the regional differences in green growth efficiency of the same type of geographical units, this paper measures the green growth efficiency and decomposition indicators of the Yangtze River Economic Belt and the Yellow River Basin from 2010 to 2020 using a three-stage DEA model and the Malmquist index method and establishes a panel Tobit model to identify the influencing factors of green growth efficiency. The results show that: ①After using the three-stage DEA model to remove the influence of external environment and stochastic factors, the mean values of green growth efficiency of Yangtze River Economic Zone and Yellow River Basin from 2010 to 2020 are 0.996 and 1.089, respectively. The change of green growth efficiency of Yangtze River Economic Zone is slightly higher than that of Yellow River Basin. ②The Malmquist indexes of the Yangtze River Economic Belt and the Yellow River Basin have generally increased, with the Technological Progress Index, which characterizes technological innovation, being the main endogenous driver of green growth efficiency in the Yellow River Basin, while the technical efficiency index, which characterizes factor mix and management level, is more significant in the Yangtze River Economic Belt. ③The Tobit model regression results show that the factors influencing green growth efficiency are also different in the two regions. Among them, the urbanization rate has a significantly positive effect on the two regions, while the effects of environmental regulation and research intensity are not significant. External openness has a suppressive effect on green growth efficiency in the Yangtze River Economic Belt, while the level of financial development and human capital negatively affect green growth efficiency in the Yellow River Basin. Therefore, green development in the new era should pay attention to the differences between different regions, and make appropriate development policies according to the local conditions of the development status of different regions.

1. Introduction

The basin economic belt is a new spatial subject of China's regional economic development to a higher stage, among which the Yangtze River Economic Belt and the Yellow River Basin are important economic regions and ecological barriers in China, as well as important carriers of China's future high-quality development. The Yangtze River Economic Belt covers 11 provinces in China, and its total economic volume exceeds 40% of the country in 2020, occupying an important position in the high-quality development of Chinese society (Fang et al., 2022). The Yellow River Basin, which contains 9 provinces and regions, is an important ecological security barrier in China. The total population of the Yellow River Basin accounts for 29% of the country in 2020, and its regional GDP also reaches 25% of the country, making it an important area for population activities and economic development. Since the reform and opening up, the Yangtze River economic zone has continued to develop at a high speed, and the traditional economic-oriented rough development model has neglected the importance of ecological

* Corresponding author.
E-mail address: jp510722@163.com (P. Jiang).

[1] These authors contributed equally to this work and should be considered co-first authors.

https://doi.org/10.1016/j.ecolind.2023.110214
Received 26 November 2022; Received in revised form 22 March 2023; Accepted 1 April 2023
Available online 8 April 2023
1470-160X/

environmental protection and efficient use of resources, which has seriously hindered the coordinated and sustainable development of the region. The Yellow River Basin is constrained by the level of product development and man-made destruction, and its ecological carrying capacity is also weakening, with the industrial transformation and upgrading facing greater resource constraints and a lack of sufficient adaptive capacity for innovation-driven and green growth.Table 1.

With ecological civilization and green development on the agenda, regional development is gradually moving away from the traditional single economy-oriented model, with more emphasis on green, coordinated, and sustainable. Relying on China's two longest rivers, promoting the development of the Yangtze River Economic Belt and the ecological protection and high-quality development of the Yellow River Basin have been promoted as major national strategies. In November 2020, General Secretary Xi Jinping hosted a symposium on promoting the development of the Yangtze River Economic Belt in Nanjing, emphasizing the need to practice the new development concept and promote the high-quality development of the Yangtze River Economic Belt. In 2021, the Plan for Ecological Protection and High-Quality Development of the Yellow River Basin The Outline also proposes to make the Yellow River Basin an important benchmark for the management of large rivers. But at present, the Yangtze River Economic Zone and the Yellow River Basin still have many problems such as large pollution emissions, a fragile le ecological environment, and outstanding environmental risks. Relying on the "big rivers" to implement major national development strategies and exploring green growth paths in line with local characteristics according to local conditions is an inevitable choice to achieve sustainable development and high quality in the two regions.

Green growth efficiency is an important indicator to measure the level of green growth. The primary problem facing the research on green development in the two regions is to accurately measure the green growth efficiency and analyze it based on measurement results, to upload and evaluate the current situation, characteristics, and differences of green development in the two regions in general and provide data support for the subsequent related research. From the existing studies, there is still a need to expand the regional perspective and measurement methods. Against the above background, this paper follows the research idea of "overall difference - sub-item difference - cause identification". Based on the scientific measurement of green growth efficiency in the Yangtze River Economic Belt and the Yellow River Basin, we analyze the spatial and temporal differences of green growth inefficiency in the two regions in a multi-dimensional manner and identify the influencing factors to explore the synergistic path of green growth and ecological civilization construction in the Yangtze River Economic Belt and the Yellow River Basin, to provide theoretical support for the implementation of national strategies for regional high-quality and sustainable development.

Table 1
Green growth efficiency index system.

Variable Type	Indicators	Description	Data sources
Input Variables	Labor input	Number of employees at the end of the year (Zhao et al., 2022b)	*Demographic and Employment Statistics Yearbook* (2010–2020)
	Capital input	Total social fixed asset investment (LIU and QIN, 2019; LU et al., 2016)	2010–2020 19 provinces (cities) statistical yearbook
	Energy input	Total energy consumption (Shuai and Fan, 2020)	*China Energy Statistics Yearbook* (2010–2020)
	Environmental input	Pollutant emissions (Qu et al., 2022; Xiang and Gu, 2022)	*China Environment Statistical Yearbook* (2010–2020)
Output Variables	Economic output	Real GDP(Wu et al., 2020)	*China Statistical Yearbook* (2010–2020)
	Economic Environment	GDP per capita(Zhong et al., 2022)	*China Statistical Yearbook* (2010–2020)
Environmental factors	Social Environment	Industry Structure (Zhao et al., 2020)	2010–2020 19 provinces (cities) statistical yearbook
	Institutional Environment	General fiscal budget expenditure as a percentage of regional GDP (Chen et al., 2021)	2010–2020 19 provinces (cities) statistical yearbook

2. Review of the literature

The traditional sloppy economic growth is characterized by high energy consumption, high emissions, and high pollution at the expense of the environment, and is also known as grey growth or black growth. In 2005, the United Nations Economic and Social Commission for Asia and the Pacific (UNESCAP) first introduced the concept of "green growth". Green growth has been defined as a key strategy for achieving low-carbon and sustainable economic growth and has since been enriched in meaning.

As the concept of green growth continues to evolve, more and more scholars are engaged in the study of green growth. According to scholars, green growth represents an attempt to promote economic growth in a way that balances environmental hazards with long-term economic growth. (Michael and Marien, 2011). Unlike green development and the green economy, green growth places greater emphasis on relying on innovation and technology to achieve harmonious economic and ecological development (Shang et al., 2020). From the perspective of research methods, the measurement methods for green growth are mainly divided into two categories, one is to measure the level of green growth through the evaluation index system, and scholars have constructed a green growth evaluation index system through the subjective assignment method and the objective assignment method (Casadio Tarabusi and Guarini, 2018). Green growth is measured in a dual dimension of time and space. Examples include the OECD's Green Growth Indicator System, WB's Green Growth Policy Evaluation Indicator, and UNEP's Inclusive Green Economy Measure. The other category measures green growth efficiency through stochastic frontier analysis (SFA) (JIN et al., 2018; Yuan et al., 2017) and data envelopment analysis (DEA) (Jiao et al., 2018; Li et al., 2022; Meng, 2022; ZHANG et al., 2016; ZHANG and SUN, 2018; Zhao and Yang, 2017). It also adds resource and environmental factors to the traditional measurement indicators, making the measurement results more scientific and reasonable. In addition, several scholars have conducted extensive research on the factors (Zhao et al., 2022b) and mechanisms influencing the efficiency of green growth. Scholars have found significant differences in the effects of environmental regulation (Liu, 2013; Zhao et al., 2022c), economic development (Lin and Zhou, 2022; Luo et al., 2022), industrial structure (Cheng and Jin, 2022; Li and Ma, 2021), technological innovation (Cao et al., 2022), financial development (XIE and LIU, 2019; Zhao et al., 2022a), digitalization (Hao et al., 2023; Shen et al., 2022), and openness to the outside world (SUN et al., 2014) on the efficiency of green growth using Tobit (Shuai and Fan, 2020), Difference-in-Differences (DID)(Liu et al., 2022).

In terms of study regions, scholars have explored the green growth efficiency of countries (Baniya et al., 2021; Cheng et al., 2021; Hao et al., 2021; Luukkanen et al., 2019; Ofori et al., 2022), regions (JIA et al., 2021; Zhang et al., 2021), city clusters (Jiao et al., 2018; Ma et al., 2019; Zhao et al., 2022b)and different provinces (Li et al., 2022; Meng and Shao, 2020), not the least of which is the measurement and study of the overall green growth efficiency of the Yangtze River Economic Belt (SUN et al., 2018)and the Yellow River Basin (Meng, 2022). In summary, scholars have conducted a large number of studies on green growth efficiency from different perspectives and in different regions, which provide useful references for this paper. However, the existing studies still have the following shortcomings: First, the research methods are used to ignore the influence of external environmental factors on the results, which often results in certain measurement errors. Secondly, fewer studies compare and analyze the differences in green growth efficiency between the Yellow River Basin and the Yangtze River Economic Belt. Based on this, this paper adopts a three-stage DEA model to measure the green growth efficiency values of the Yangtze River Economic Belt and the Yellow River Basin to make the results obtained more scientific and accurate, and combines the Malmquist index to identify the differences between the two in multiple dimensions, and finally constructs a panel Tobit model to identify the influencing factors of green growth efficiency. The aim is to suggest countermeasures for green growth in the Yangtze River Economic Belt and the Yellow River Basin through the above work.

3. Selection of indicators and data sources

3.1. Selection of indicators

In general, when using the DEA model for efficiency analysis, the number of decision units is required to be at least twice the number of variables (the sum of input and output variables). In terms of indicator selection, based on the new economic growth model, labor and capital are the most basic factors of production, but the traditional efficiency measurement process does not take into account energy and environmental factors (YANG and DU, 2015), which makes the measurement results biased. Considering the increasingly prominent ecological and environmental constraints and energy supply shortages, the measurement of green growth efficiency needs to be based on the traditional growth efficiency measurement indicators, including energy and environmental factors to build a more comprehensive and comprehensive indicator to measure (LU et al., 2019). The output of green growth efficiency is mainly determined by labor input (L), capital input (K), energy input (E) and environmental input (O), and the corresponding output function is: Y = f(L, K, E, O). Where the input variables: ①Labor inputs, using the number of employees at the end of the year (Zhao et al., 2022b) (ten thousand people); ②Capital Inputs (LIU and QIN, 2019; LU et al., 2016). Using the total social fixed asset investment (billions); ③Energy inputs (Shuai and Fan, 2020). Total energy consumption used (million tons of standard coal); ④Environmental inputs. Industrial "three wastes" emissions are used as the opportunity cost of environmental pollution lost in the social production process, and the most representative wastewater emissions, sulfur dioxide and smoke (dust) emissions are weighted by the entropy weighting method to obtain a comprehensive indicator - pollutant emissions (Qu et al., 2022; XIANG and GU, 2022). The output variable uses the real GDP of the 19 provinces in the region calculated using 2010 as the base period (Wu et al., 2020).

Environmental variables are those elements that can influence the efficiency of green growth, but which the sample cannot subjectively control and change. In this paper, the corresponding environmental variables are selected from three aspects: economic environment, social environment, and institutional environment, based on the existing relevant studies. The economic environment variable was selected as GDP per capita (Zhong et al., 2022), the higher the GDP per capita, the higher the level of economic development of the city and the better the macroeconomic environment. The industrial structure was chosen to represent the social environment variables (Zhao et al., 2020). Measured by the value added of the tertiary sector as a proportion of GDP, because the industrial structure plays an important role in the coordination between the economy, society, and the ecological environment, the tertiary sector, led by the service industry, is the main direction of industrial restructuring and upgrading. Institutional environment variable selection of general fiscal budget expenditure as a share of regional GDP (Chen et al., 2021). It measures the degree of government financial support to the region, the greater the government support regulation, the more conducive to local ecological management and green development.

3.2. Research methodology

3.2.1. Three -stage DEA

Phase 1: Super-SBM model. Due to the limitations of the traditional DEA model, when multiple decision units are valid at the same time, they cannot be further differentiated and compared. To address this limitation, Anderson and Peterson developed an improved super-efficient DEA model, which can rank and compare decision units with efficiency values greater than 1. However, the model is susceptible to extreme values that amplify differences in efficiency, and conclusions can be biased. Tone (Tone, 2002) proposed a non-radial, non-angular SBM model, which is based on slack variables of Super-efficiency solves the problem of input factor redundancy caused by the radial DEA model metric. This paper, therefore, chooses the input-oriented super-efficient SBM model, which focuses on the extent of adjustment required to achieve an effective DMU for each input without reducing output. The Super-SBM model considering the slack variables takes the following form:

$$\gamma^* = min\frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^x}{x_{i0}}}{1+\frac{1}{q+r}\left(\sum_{p=1}^{q}\frac{s_p^y}{y_{p0}}+\sum_{k=1}^{r}\frac{s_k^b}{b_{k0}}\right)}$$

$$\begin{cases} \sum_{j=1,j\neq 0}^{n} x_{ij}\lambda_j \leq x_{i0}+s_i^x (i=1,2,3,\cdots,m) \\ \sum_{j=1,j\neq 0}^{n} y_{pj}\lambda_j \geq y_{p0}-s_p^y (p=1,2,3,\cdots,q) \\ \sum_{j=1,j\neq 0}^{n} b_{kj}\lambda_j \leq b_{k0}+s_k^b (k=1,2,3,\cdots,r) \\ \sum_{j=1}^{n}\lambda_j = 1(VRS) \\ \lambda_J \geq 0, s_I^X \geq 0, s_p^y \geq 0, s_k^b \geq 0 \end{cases}$$

In the formula:s_i^x, s_p^y and s_k^b, they represent slack variables for inputs, consensual outputs, and non-consensual outputs respectively, i.e. the amount by which inputs and outputs can be further optimally improved;λ represents Linear programming weight vector;VRS denotes variable returns to scale;x_{io} is the total number of inputs of the o-th decision unit to the i-th category of inputs, the rest of the variables can be analogous; y^* represents the green growth efficiency value. Assume that the production system has n homogeneous DMUs, each utilizing m inputs and producing q desired outputs and r undesired outputs, whose elements can be represented $x \in R^m, y \in R^q, b \in R^r$. When $\gamma^* < 1$, the DMU is in an invalid situation and the inputs or outputs are not justified, when $\gamma^* \geq 1$, DMU achieves effectiveness.

In the first stage, the unadjusted initial efficiency values and input redundancy of the decision units were calculated from the input perspective. Although this method avoids the bias caused by radial DEA, the measured results attribute all the influencing factors to the internal management level. Because of this, in the second stage, this paper combines Freid's research with the construction of a similar stochastic frontier SFA model to remove external environmental factors and adjust the inputs according to the results. The SFA model allows for the decomposition of the slack variables into environmental factors, management inefficiency, and statistical noise. Specifically, the slack variables from the traditional DEA model in the first stage were used as the explanatory variables, the environmental factors were used as the explanatory variables, and the SFA regression model was constructed:

$$s_{ij} = f^j(z_i, \beta_j) + v_{ij} + u_{ij}(i = 1, 2, \cdots, N; j = 1, 2, \cdots, P)$$

In the formula, s_{ij} denotes the slack value of the j-th input of the i-th decision unit, z_i is the environmental variable, β_j is the coefficient of the environmental variable, $v_{ij}+u_{ij}$ are mixed error terms, v_{ij} represents the effect of random disturbances on input slack variables and v_{ij} $N(0,\sigma^2{}_{iv})$, u_{ij} represents the effect of management factors on input slack variables, which follow a half-normal distribution and u_{ij} $N^{+}(\mu^j,\sigma^2{}_{ju})$.

Based on the results of the stochastic frontier analysis, all decision units were adjusted to the same external environment by removing the interfering effects of environmental and stochastic factors on the efficiency values, and the adjustment formula was as follows.

$$X^A{}_{ni} = X_{ni} + [max(f(Z_i:\beta_n)) - f(Z_i:\beta_n)] + [max(v_{ni}) - v_{ni}](i = 1,2,\cdots,I; n = 1,2,\cdots,N)$$

In the formula,$X^A{}_{ni}$ and X_{ni} denote the adjusted and pre-adjusted inputs respectively,$max(f(Z_i:\beta_n)) - f(Z_i:\beta_n)$ is an adjustment for environmental factors, $max(v_{ni}) - v_{ni}$ means adjusting all decision units to the same random disturbance condition. By controlling for the same environmental factors and random disturbances, the effect of both on the efficiency measurement of the decision unit is avoided, ensuring that the adjusted efficiency measure reflects the true level of the decision unit.

Stage 3: After completing the regression analysis of the second stage SFA model, the adjusted input values are substituted for the original input values, and the efficiency values of each decision unit are measured again in the first stage Super-SBM model so that the efficiency values can be obtained without the influence of environmental variables and random errors.

3.2.2. Malmquist index

Since the three-stage DEA model can only analyze the efficiency values of decision units from a static perspective, to explore the dynamic changes, this paper combines the analysis with the Malmquist index, which is calculated as follows.

$$\mathrm{M}(x_t, y_t, x_{t+1}, y_{t+1}) = \sqrt{\frac{D^t(x_{t+1}, y_{t+1})}{D^t(x_t, y_t)} \times \frac{D^{t+1}(x_{t+1}, y_{t+1})}{D^{t+1}(x_t, y_t)}}$$

If the Malmquist index is greater than one, it indicates an improved level of green growth efficiency, while the opposite indicates a decline. The Malmquist decomposition gives the Technical Efficiency Index (Effch) and the Technological Progress Index (Techch).

$$\mathrm{M} = (x_t, y_t, x_{t+1}, y_{t+1}) = \frac{D^{t+1}(x_{t+1}, y_{t+1})}{D^t(x_t, y_t)} \sqrt{\frac{D^t(x_{t+1}, y_{t+1})}{D^{t+1}(x_{t+1}, y_{t+1})} \times \frac{D^t(x_t, y_t)}{D^{t+1}(x_t, y_t)}}$$

In the above formula: The first represents the Technology Progress Change Index (Techch); the second represents the Technology Efficiency Change Index (Effch); Effch reflects whether existing technology is being used effectively in the decision unit. If Effch greater than 1, it indicates that the level of technology within the decision unit has improved better between the beginning and end of the period; Techch represents the impact of technological progress on the efficiency of green growth, and a value greater than 1 indicates that technological innovation has been achieved.

3.2.3. Panel Tobit model

The green growth efficiency of each region measured by the Super-SBM model above is non-negative truncated discrete data, and the use of ordinary least squares may lead to biased parameter estimates, so it is appropriate to use the panel Tobit model for regression analysis, and its regression model is as follows The regression model is as follows.

$$Y_{it} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon_i$$

In the above formula,Y_{it} is the dependent variable(the green growth efficiency value of the i-th province in year t),X_n is the independent variable,β_0 is the intercept direction,β_n is the regression coefficient of the respective variable,ε_i is the error term.

4. Green growth efficiency measurements in the Yangtze River Economic Belt and the Yellow River Basin

4.1. Phase 1 DEA results analysis

The Super-SBM model was used to analyze the green growth efficiency of 9 provinces in the Yellow River Basin and 11 provinces in the Yangtze River Economic Belt from 2010 to 2020, and the results are shown in Tables 2–3.

In terms of the basin as a whole, the average value of green growth efficiency in the Yangtze River Economic Belt was 0.985 during 2010–2017, compared to 1.137 in the Yellow River Basin, with the average value of green growth efficiency in the Yellow River Basin being slightly higher than that of the Yangtze River Economic Belt. Green growth efficiency was better overall. Among them, from 2010 to 2015, the average value of green growth efficiency in the Yellow River Basin decreased from 1.123 to 1.077 respectively, with a smaller decrease; from 2015 to 2020, the average value of green growth efficiency in the Yellow River Basin increased by 0.147, with a larger increase. In contrast, the average value of green growth efficiency in the Yangtze River Economic Belt changed little overall over the 11-year period and was relatively stable.

From within the river basin, the green growth efficiency of the Yangtze River Economic Belt from 2010 to 2021 is on the whole midstream $<$ upstream $<$ downstream, showing the spatial distribution characteristics of low in the middle and high on both sides, with uneven green development in different regions. The green growth efficiency of Shanghai is the highest, with an average efficiency value of 1.956, while that of Anhui is the lowest, with an average efficiency value of 0.448. There is a wide gap between the green growth efficiency of different provinces. Compared to the Yangtze River Economic Belt, the regional disparity in green growth efficiency in the Yellow River Basin is smaller, with five provinces, including Inner Mongolia, Sichuan, and Gansu, having higher and increasing green growth efficiency, reflecting the better results achieved in the construction of the ecological environment in southwest China. As the first stage of DEA analysis did not exclude the influence of external environmental factors and random disturbances, it could not accurately reflect the actual situation of green growth efficiency of provinces (cities). To further understand the real green growth efficiency, the following stochastic frontier model is used to exclude environmental factors and random disturbances in order to obtain more objective green growth efficiency data.

4.2. Stage 2 SFA regression analysis

In order to exclude the effects of environmental factors and random disturbances, the slack variables of each input variable obtained from the first stage of DEA analysis were used as dependent variables, and the environmental constraint variables of three aspects, namely economic, social and institutional, were used as independent variables, and the SFA model was used for parameter estimation to analyze whether the environmental constraint variables had significant effects on the slack variables of each input variable. The results of the second stage of SFA model parameter estimation are shown in Table 4.

As can be seen from Table 4, the coefficients of most of the environmental constraint variables are highly significant in the SFA parameter estimation of green growth efficiency, indicating that external environmental factors have a significant impact on green growth efficiency in the nineteen provinces (districts) within the two regions. Meanwhile, the γ values of each input slack variable are close to 1 and pass the 1% significance test, indicating that the influence of internal management inefficiency plays a much larger dominant role in the redundancy of input variables than the influence of random factors. The overall results of the SFA parameter estimation indicate that the

Table 2
Green growth efficiency of provinces in the Yangtze River Economic Belt, 2010–2020.

Provinces	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Average value
Shanghai	2.110	1.890	1.897	1.816	1.864	1.882	1.893	2.147	2.212	2.032	1.770	1.956
Jiangsu	1.494	1.522	1.552	1.572	1.588	1.595	1.598	1.589	1.583	1.573	1.575	1.568
Zhejiang	1.022	1.000	0.838	0.843	0.835	0.829	0.815	0.785	0.772	0.770	0.790	0.845
Anhui	0.539	0.446	0.443	0.443	0.435	0.444	0.468	0.401	0.391	0.419	0.496	0.448
Jiangxi	1.081	0.652	0.643	0.645	0.623	0.679	0.670	0.655	0.642	0.638	0.577	0.682
Hubei	0.453	0.436	0.452	0.513	0.518	0.552	0.629	0.533	0.532	0.575	0.503	0.518
Hunan	0.453	0.439	0.442	0.497	0.511	0.552	0.611	0.524	0.529	0.580	0.719	0.533
Chongqing	1.041	1.176	1.147	1.155	1.155	1.086	1.072	1.068	1.061	1.059	1.134	1.105
Sichuan	0.411	0.480	0.538	0.589	0.568	0.587	1.163	0.570	0.576	1.012	1.204	0.700
Guizhou	1.593	1.337	1.208	1.197	1.053	1.095	1.446	1.179	1.143	1.183	1.055	1.226
Yunnan	0.699	0.391	0.401	0.435	0.457	0.405	0.440	0.353	0.330	0.360	1.017	0.481
Average value	0.991	0.888	0.869	0.882	0.873	0.882	0.982	0.891	0.888	0.927	0.985	0.915
Upstream areas	0.936	0.846	0.824	0.844	0.808	0.793	1.030	0.792	0.777	0.904	1.102	
Midstream areas	0.632	0.493	0.495	0.525	0.522	0.557	0.594	0.528	0.524	0.553	0.574	
Downstream areas	1.542	1.471	1.429	1.410	1.429	1.435	1.436	1.507	1.523	1.458	1.378	

Table 3
Green growth efficiency of the Yellow River Basin provinces, 2010–2020.

Provinces	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Average value
Shanxi	0.822	1.012	0.789	0.734	0.749	0.640	0.643	1.181	1.056	1.045	1.029	0.882
Inner Mongolia	1.230	1.213	1.267	1.211	1.182	1.289	1.401	1.285	1.355	1.332	1.397	1.287
Shandong	1.696	1.681	1.675	1.684	1.681	1.677	1.669	1.662	1.644	1.621	1.657	1.668
Henan	0.831	1.015	1.023	0.846	0.841	1.011	1.015	1.253	1.296	1.322	1.066	1.047
Sichuan	0.811	0.861	1.012	1.028	1.023	1.029	1.160	0.916	0.895	0.875	1.118	0.975
Shaanxi	1.076	1.123	1.130	1.093	1.096	1.066	1.025	0.927	0.930	0.898	1.001	1.033
Gansu	1.044	0.817	0.807	0.760	0.768	0.778	0.638	1.058	1.060	1.076	1.309	0.920
Qinghai	1.586	1.492	1.372	1.372	1.353	1.365	1.172	1.417	1.436	1.446	1.336	1.395
Ningxia	1.013	1.012	1.009	1.002	1.001	0.838	1.004	1.023	1.102	1.179	1.105	1.026
Average value	1.123	1.136	1.120	1.081	1.077	1.077	1.081	1.191	1.197	1.199	1.224	1.137
Upstream areas	1.114	1.045	1.050	1.041	1.036	1.003	0.993	1.103	1.123	1.144	1.217	
Midstream areas	1.042	1.116	1.062	1.013	1.009	0.998	1.023	1.131	1.114	1.091	1.143	
Downstream areas	1.264	1.348	1.349	1.265	1.261	1.344	1.342	1.458	1.470	1.471	1.362	

Table 4
Green growth efficiency in Yangtze River Economic Belt and Yellow River Basin (results of SFA parameter estimation in the second stage).

Input slack variables	Fixed asset investment amount Slack variables	Number of employed persons Slack variables	Energy consumption Slack variables	Pollutant emission slack variables
Constant term	5250.76**	5074.97***	11244.61***	21718.43***
Fiscal spending/GDP	−19157.45	−1141.86	−3754.09***	−18712.13***
GDP per capita	0.14***	0.00	0.00	0.05
Industry Structure	213.11***	−50.25***	−138.43***	−154.36***
sigma-squared	100346240.00	1888918.60	6899291.00	86722691.00
gamma (γ)	0.89***	0.92***	0.87***	0.78***
Log value	−2045.74	−1590.60	−1790.09	−2078.40
LR test value	197.99***	260.59***	157.96***	113.03***

(Note: "*", "**", and "****" indicate significant at the 10%, 5%, and 1% levels, respectively).

external environmental factors and random errors from three aspects - economic, social, and institutional - have a significant impact on the efficiency of green growth in the nineteen provinces (cities) and that the second stage of adjustment is reasonable and necessary.

According to the basic principle of SFA parameter estimation, when the regression coefficient is negative, it indicates that the environmental constraint variable can reduce the input redundancy, i.e. increasing the environmental constraint variable helps to improve the green growth efficiency; when the regression coefficient is positive, the increase of the environmental constraint variable does not help to reduce the input redundancy, then it does not help to improve the green growth efficiency. Looking specifically at the effect of each environmental constraint variable on the redundancy of input variables.

(1) The effect of general fiscal budget expenditure as a share of GDP. Institutional environmental factors only have a significant impact on energy consumption and pollutant emissions, both of which are negative. Specifically, local general fiscal budget expenditures are mainly spent on science and technology innovation, education, social security and employment, healthcare, environmental protection, agriculture, forestry and water affairs, transportation, etc. The increase in general fiscal budget expenditures in the Yellow River Basin and Yangtze River Economic Belt can be invested more in local energy conservation and emission reduction, ecological protection, and by strengthening government influence and increasing support for enterprises, the Improve the initiative of enterprises to carry out energy conservation and emission reduction in the production process, which in turn can improve the efficiency of enterprise energy use, reduce energy consumption and lower pollutant emissions, thus promoting the efficiency of green growth.

(2) The effect of GDP per capita. GDP per capita only affects the amount of investment in fixed assets and pollutant emissions. The effect on the amount of investment in fixed assets is positive and passes the 1% significance test, but the effect on pollutant emissions is not significant. To a certain extent, GDP per capita reflects the degree of regional

economic development. A higher GDP per capita means a higher level of economic development in the region and therefore more investment in fixed assets for planning, development, and investment in the region. An increase in GDP per capita will lead to an increase in the slack variable of capital investment, thus reducing the efficiency of capital utilization. This is mainly due to the threshold effect of increasing GDP per capita on capital efficiency (GUO et al., 2018), When the threshold value is below, the increase in GDP per capita will not have a positive impact on capital efficiency, which will have a negative impact on environmental efficiency.

From a specific regional perspective, the upper and middle reaches of the Yangtze River Economic Belt are relatively lagging economically. They have taken over the transfer of some high-emission industries from the eastern regions due to their abundant labor factors and higher environmental carrying capacity, thus making their fixed asset investments concentrated in labor-intensive industries and high-carbon emission industries. Compared with the Yangtze River Economic Belt, the Yellow River Basin is more backward in terms of economic development and more fragile in terms of ecological environment. At the same time, most of the fixed asset investments in the Yellow River Basin are confined to heavy chemical and real estate development industries. The damage to the natural ecological environment caused by such disorderly and excessive development can be seen in incidents such as the environmental destruction of the Qilian Mountains in Gansu and the illegal construction of the Qinling Mountains in Shaanxi.

(3) The influence of industrial structure. The impact of industrial structure on the amount of investment in fixed assets is positive, while the impact on the number of people employed, total energy consumption, and pollutant emissions are all negative, and all pass the significance test. At present, the industrial structure of the Yangtze River Economic Belt and the Yellow River Basin is constantly being adjusted but the overall efficiency is not high. There is a large gap between the rationalization of the industrial structure in the lower reaches of the Yangtze River Economic Belt and the middle and upper reaches. In particular, the tertiary sector in the midstream region started late and accounts for a low share of the economy. Similarly, the Yellow River Basin faces the problem of unreasonable industrial structure and weak development of the tertiary industry in many provinces. The rise of the tertiary sector requires large amounts of financial support to accelerate the acquisition of investment, thus creating redundancy in fixed asset investment.

The development of the tertiary industry is conducive to absorbing more labor and relieving regional employment pressure, which naturally reduces the amount of redundancy in labor input. In addition, the development of the tertiary industry is conducive to the transformation and upgrading of the industrial structure. Generally speaking, the primary industry, which is mainly agriculture, will pollute the land and water resources due to inputs such as chemical fertilizers and pesticides, thus affecting the ecological environment. The secondary industry, mainly industry, requires large amounts of energy input and emits large amounts of wastewater, exhaust gas, sulfur dioxide, and other polluting waste. The tertiary industry, mainly the service industry, consumes less energy and emits less. The rise of the tertiary industry has reduced the economic share of the primary and secondary industries, thus contributing to lower energy consumption and reduced pollutant emissions. The upgrading of the industrial structure is therefore conducive to reducing the level of redundancy in energy consumption and pollutant emissions.

4.3. Analysis of Phase 3 results

The original input variables were data corrected according to the SFA parameter estimation results and measured again using the super-SBM model to obtain the green growth efficiency values after excluding the effects of external environmental factors and random disturbances (Tables 5-6).

Comparing the first-stage and second-stage efficiency values, it can be seen that the SFA regression model not only removes the influence of environmental variables and random factors but also makes the measured efficiency values more realistic. When comparing the two, it is found that, overall, the mean green growth efficiency value of the Yangtze River Economic Belt has increased compared to the mean efficiency value of the first stage, while the mean efficiency value of the Yellow River Basin has decreased, indicating that environmental factors have a significant impact on green growth efficiency during the period 2010–2020. Therefore, the use of stochastic frontier analysis is necessary to remove environmental factors and random disturbances. However, as the ideas of green and sustainable development and high-quality development receive more attention in economic development, the impact of environmental factors on green growth efficiency gradually decreases. Among them, the overall change in the Yangtze River Economic Belt is greater, and the two stages in the Yellow River Basin have smaller changes, indicating that the green growth efficiency of the Yangtze River Economic Belt is more influenced by environmental factors.

In terms of specific provinces, analysis of Tables 5 and 6 shows that in the Yangtze River Economic Belt, the average green growth efficiency values of Shanghai, Jiangsu, Chongqing, and Guizhou in the third stage during 2010–2020 have decreased compared to the first stage, and the average efficiency values of Inner Mongolia, Henan, Shaanxi, and Qinghai in the Yellow River Basin are also lower than those of the first stage, indicating that the higher previous green growth efficiency values are attributed to their better external environment, such as a developed economic macro environment and government policy support. Anhui, Jiangxi, and Hubei provinces and cities have seen a larger increase in their average green growth efficiency values, indicating that

Table 5
Green growth efficiency of the Yangtze River Economic Belt (Results of the third stage DEA analysis).

Provinces	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Average value
Shanghai	1.101	1.072	1.048	1.038	1.053	1.057	1.060	1.090	1.103	1.104	1.057	1.071
Jiangsu	1.494	1.522	1.552	1.572	1.588	1.595	1.598	1.589	1.583	1.573	1.575	1.568
Zhejiang	1.010	0.915	1.001	1.001	1.001	1.001	1.001	1.001	0.962	1.000	0.993	0.990
Anhui	0.835	0.769	0.783	0.802	0.816	0.835	0.850	0.843	0.845	0.849	0.869	0.827
Jiangxi	1.038	0.901	1.000	1.000	1.001	1.000	1.000	1.000	1.001	1.001	1.002	0.995
Hubei	0.886	0.919	0.951	0.975	0.968	0.979	1.001	0.972	0.968	0.969	0.954	0.958
Hunan	0.878	0.909	0.930	0.963	0.967	1.001	1.001	1.000	0.957	0.962	1.000	0.961
Chongqing	1.019	1.044	1.047	1.043	1.043	1.033	1.024	1.019	1.019	1.026	1.056	1.034
Sichuan	0.702	0.748	0.746	0.781	0.755	0.765	1.059	0.795	1.009	1.046	1.059	0.860
Guizhou	1.074	1.057	1.035	1.045	1.016	1.030	1.067	1.045	1.037	1.041	1.011	1.042
Yunnan	0.823	0.490	0.507	0.542	0.587	0.546	0.580	0.547	1.001	0.560	1.005	0.653
Average value	0.987	0.940	0.964	0.978	0.981	0.986	1.022	0.991	1.044	1.012	1.053	0.996
Upstream areas	0.905	0.835	0.834	0.853	0.850	0.843	0.933	0.851	1.016	0.918	1.033	
Midstream areas	0.909	0.875	0.916	0.935	0.938	0.954	0.963	0.954	0.943	0.945	0.956	
Downstream areas	1.202	1.169	1.200	1.204	1.214	1.218	1.220	1.227	1.216	1.226	1.208	

Table 6
Green growth efficiency in the Yellow River Basin (results of the third stage DEA analysis).

Provinces	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Average value
Shanxi	1.003	1.004	1.001	0.988	0.862	0.711	0.743	1.025	1.008	1.007	1.005	0.941
Inner Mongolia	1.068	1.072	1.059	1.035	1.054	1.094	1.093	1.084	1.100	1.096	1.090	1.077
Shandong	1.696	1.681	1.675	1.684	1.681	1.677	1.669	1.662	1.644	1.621	1.657	1.668
Henan	0.984	1.011	1.017	1.000	0.996	1.008	1.012	1.120	1.120	1.131	1.041	1.040
Sichuan	0.996	0.977	1.007	1.015	1.011	1.015	1.067	0.996	0.996	0.994	1.038	1.010
Shaanxi	1.043	1.040	1.068	1.054	1.053	1.041	1.019	1.003	1.002	1.002	1.003	1.030
Gansu	1.014	1.002	0.993	0.895	0.896	0.872	0.878	1.009	1.011	1.013	1.037	0.965
Qinghai	1.073	1.074	1.057	1.057	1.052	1.011	1.034	1.082	1.092	1.101	1.096	1.066
Ningxia	1.005	1.006	1.007	1.005	1.004	1.007	1.005	1.004	1.009	1.014	1.012	1.007
Average value	1.098	1.096	1.098	1.082	1.068	1.048	1.058	1.109	1.109	1.109	1.109	1.089
Upstream areas	1.022	1.015	1.016	0.993	0.991	0.976	0.996	1.023	1.027	1.030	1.046	
Midstream areas	1.038	1.039	1.043	1.026	0.990	0.949	0.952	1.037	1.037	1.035	1.033	
Downstream areas	1.340	1.346	1.346	1.342	1.338	1.342	1.340	1.391	1.382	1.376	1.349	

environmental factors and random disturbances have had a stronger inhibiting effect on their efficiency values. Overall, there is still more room for improvement in the green growth efficiency of the Yangtze River Economic Belt and the Yellow River Basin.

To more intuitively analyze the spatial and temporal changes in green growth efficiency, the natural breakpoint method in the GIS tool was used to classify green efficiency into four categories. As the results obtained from DEA are relative values, the green growth efficiency values for each region were plotted based on 2010, 2015, and 2020 respectively.

As shown in Fig. 1. From the spatial distribution pattern, there are significant geographical differences in the green growth efficiency levels of the provinces in the Yangtze River Economic Belt and the Yellow River Basin. In the Yellow River Basin, Shandong Province has been stable in the first echelon during the sample period, while Shaanxi Province has fluctuated in changes, rising from the third echelon to the second echelon and then falling to the third echelon. While Qinghai, Inner Mongolia, and Shanxi provinces are more stable. Henan Province is even steadily rising, from the 4th tier to the 3rd tier in 2010. In the Yangtze River Economic Belt, Jiangsu and Shanghai have been stable in the first echelon, and the green growth efficiency level in the downstream region is higher and more stable, and gradually radiates to the

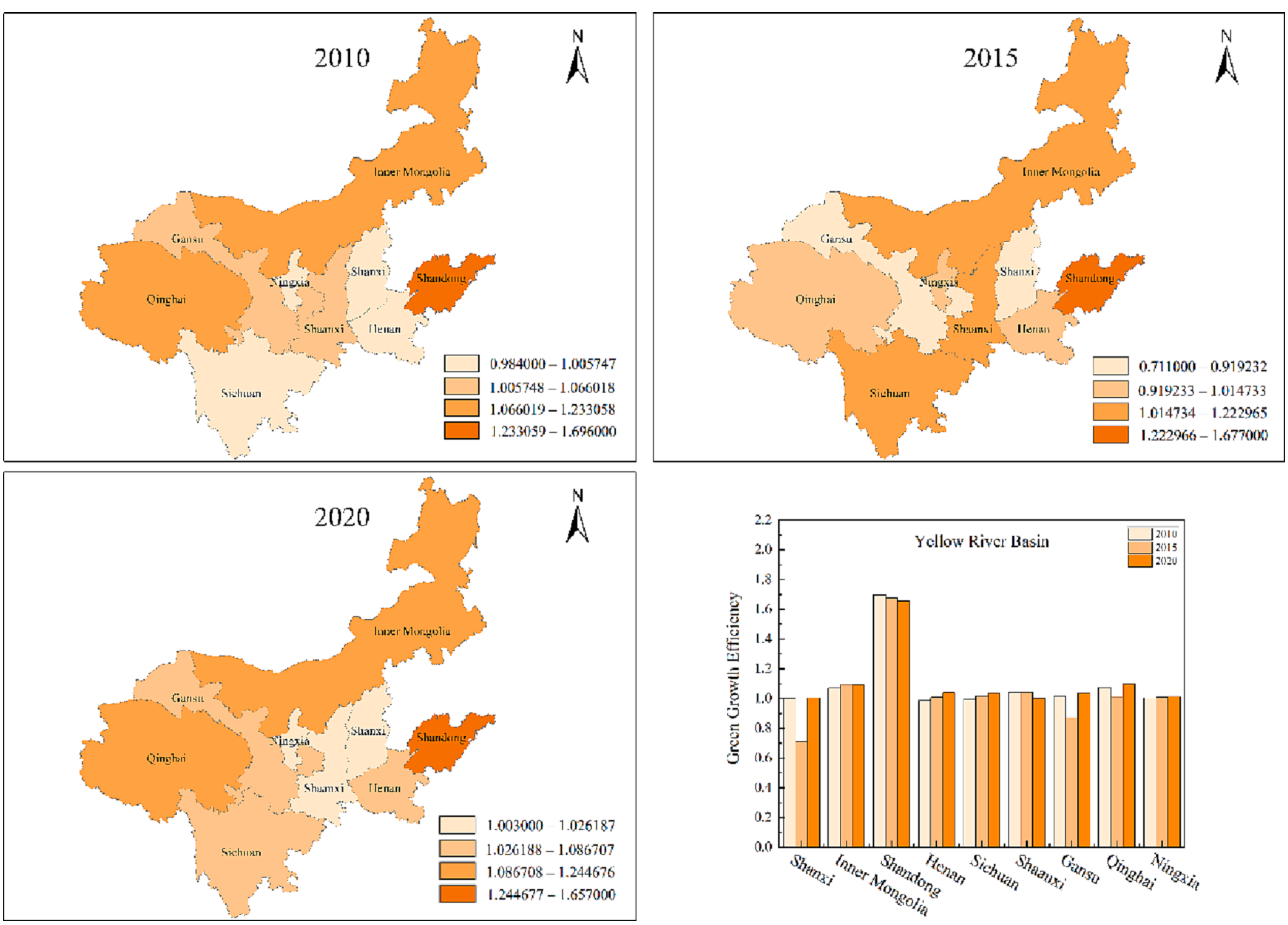

Fig. 1. Grouping of regional characteristics of green growth efficiency in the Yellow River Basin. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

midstream and downstream regions. Among them, Guizhou province belonged to the tier 1 region in 2010, dropped to the tier 2 region in 2015, and dropped to tier 3 again in 2020, and the level of green growth is lower and more volatile compared with other provinces.

5. Dynamic analysis of green growth efficiency

Given that the three-stage super-SBM measurement in the previous paper is a static analysis of the changes in green growth efficiency, to explore the dynamics of the Yangtze River Economic Belt and the Yellow River Basin and the differences in the changes in green growth efficiency at the dynamic level, this paper uses the Malmquist index to do a further dynamic evolutionary analysis of it (Fig. 2). For reasons of space, the indices for each decomposition efficiency shown in the figure are mean values.

On the whole, the overall green growth efficiency index of the Yangtze River Economic Belt shows a development trend of decline - rise - decline - rise, with an average value of 1.04. The change in the green growth efficiency of the Yellow River Basin is smaller than that of the Yangtze River Economic Belt, with an overall development trend of rising - decline - rise, with an average value of 1.02. This indicates that the green development of the Yangtze River Economic Belt and the Yellow River Basin is not fully harmonized with the ecology and environment, and there is some room for improvement.

The Malmquist index represents the dynamic change value of green growth efficiency, which can be decomposed into the technical efficiency index and the technical progress index. From Fig. 3(a) and (b), it can be seen that the technical efficiency index of the Yangtze River Economic Zone has increased, but the technical progress index has decreased overall. This indicates that the level of technical progress in the Yangtze River Economic Zone still needs to be improved. The

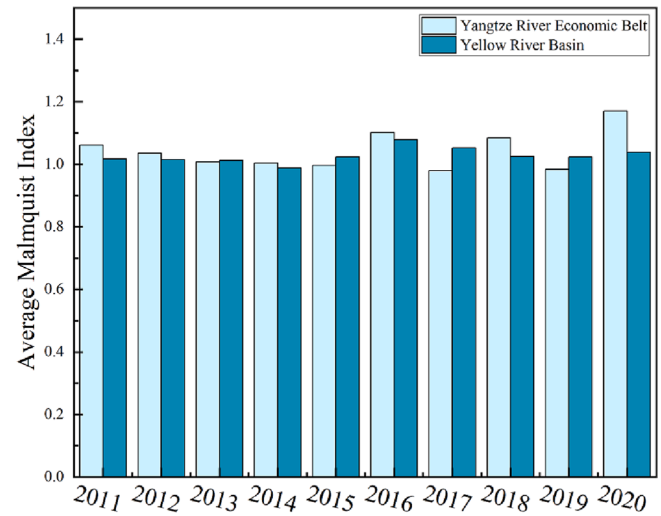

Fig. 3. Average Malmquist Index of Yangtze River Economic Belt and Yellow River Basin Provinces (Cities). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

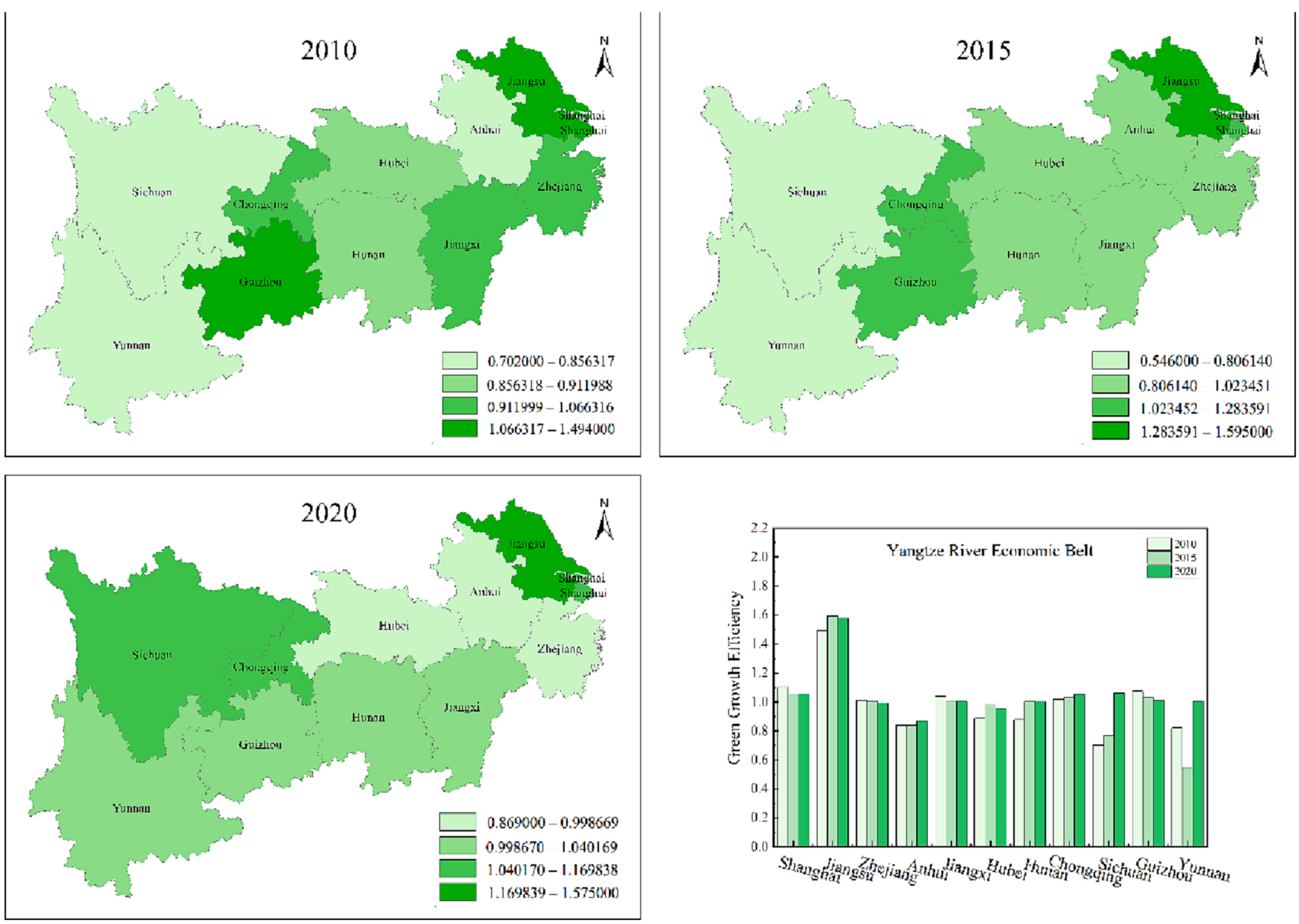

Fig. 2. Grouping of regional characteristics of green growth efficiency in the Yangtze River Economic Belt. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

technical progress index of the Yellow River Basin is greater than the technical efficiency index, which indicates that the Yellow River Basin has improved faster and the technical progress has played an obvious role in the green growth of the economy.

Malmquist indices and their decomposition values for provinces and cities in the Yellow River Basin and Yangtze River Economic Belt are given in Fig. 3(c) and (d). From the intra-regional perspective, the provinces in the Yangtze River Economic Belt and the Yellow River Basin with more significant growth in the overall green growth efficiency index include Yunnan, Guizhou, and Shandong, indicating that these three regions have optimized improvements in ecological protection, green technology development, and personnel management. Second, the overall efficiency indexes of both the middle and lower reaches of the Yangtze River Economic Belt and the Yellow River Basin are larger than those of the middle and upper reaches, probably because the lower reaches are located in coastal areas and have a more advantageous geographical position, and their green development started early and has rapidly become a concentration of finance, technology, and talent in recent years.

The Malmquist Index for the middle and lower reaches of the Yangtze River Economic Belt is mainly attributed to the growth of the Technological Progress Index(Techch), indicating that the middle and lower reaches have relatively strong technological innovation capabilities and rapid technological upgrading, while the Malmquist Index for the upper reaches relies mainly on the growth of the technical efficiency change index(Effch), probably because, as the Yangtze River Economic Belt has advanced through the Golden Waterway After the integration of economic interoperability, the pace of technology-intensive industries moving to the upstream region was accelerated, resulting in a much higher index of technical efficiency change in the upstream region. In the Yellow River Basin, on the other hand, the Technological Progress Index is the main factor influencing the green growth efficiency index in the Yellow River Basin, but the different technological conditions and economic development levels of each province (city) make the values of the decomposition index still differ significantly. The technical efficiency index of Shaanxi, Shandong, Shanghai, Zhejiang, Jiangxi, and Guizhou is less than one, and the technical progress index of Yunnan and Guizhou is less than one. Therefore, on the basis of the positive development trend, we should make the arrangement of technical input and output structure more reasonable, and continue to strengthen technological innovation and promote technological progress. Especially in the case of Guizhou, which is a “double-low” province, emphasis should be

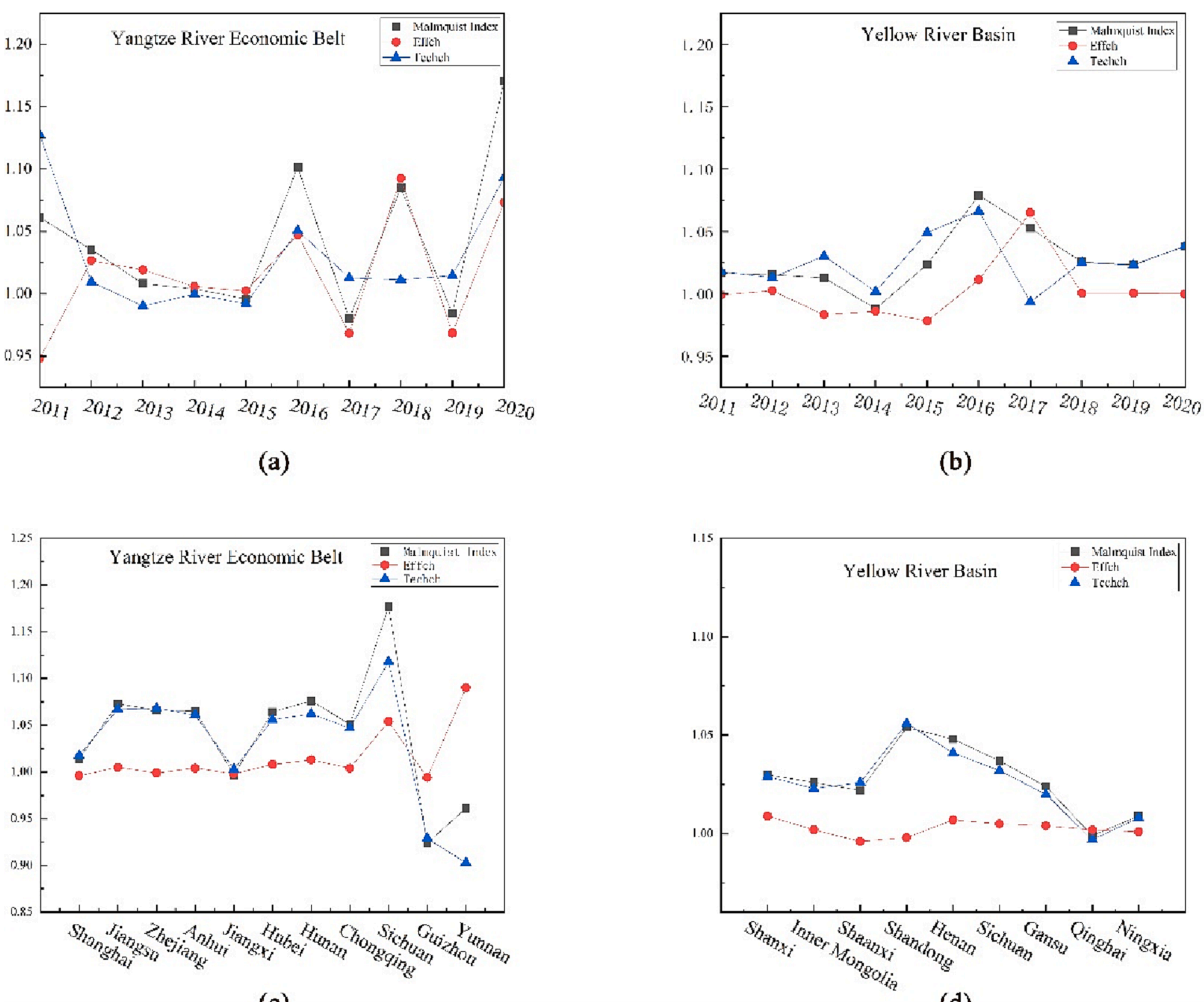

Fig. 4. Malmquist index decomposition for Yangtze River Economic Belt (left) and Yellow River Basin (right). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

placed on green innovation and further reform of the management system and industrial structure (Fig. 4).

It should be noted that the Malmquist Index for Qinghai, Jiangxi, Guizhou, and Yunnan provinces is <1. The Techch for Qinghai is 0.997 and the Techch for Yunnan is 0.903, indicating that the Malmquist Index is mainly attributed to the negative impact of technological progress, the Effch for Jiangxi is 0.998, indicating that the improvement in technological progress is affected by the decline in technological efficiency, and both decomposition values for Guizhou are below 1 In Guizhou, both decomposition values are below 1, indicating that technical efficiency and technical progress simultaneously play a negative role in the improvement of the Malmquist Index.

In summary, one of the ways to improve the efficiency of green growth in the Yellow River Basin and Yangtze River Economic Belt is to vigorously promote green technology, increase investment in scientific research, improve technology levels and promote green economic growth through technological innovation.

6. Analysis of factors influencing green growth efficiency in Yangtze River Economic Belt and Yellow River Basin

To further explore the impact of other factors on green growth efficiency, a regression analysis was conducted using the Tobit model based on the third-stage DEA model measurement, with the green growth efficiency measured by the third-stage DEA model as the dependent variable and the influencing factors as the independent variables.

6.1. Factor selection and modeling

Drawing on the existing literature, this paper selects six indicators as influencing factors of green growth efficiency. ①Urbanization rate (Shao and Wang, 2023; Zou et al., 2022). The urbanization process reflects the level of economic development of the region and contributes to the growth of the region's economic volume, but it also increases the level of environmental pollution due to the expansion of towns and cities, population concentration, and large-scale development of industry and agriculture; ②Environmental regulation intensity (Xu et al., 2022; Zhao et al., 2022c). Expressed as a share of industrial pollution investment in the value added of the secondary sector, according to the Porter hypothesis, reasonable environmental regulation is conducive to promoting technological innovation by enterprises, thus saving energy, reducing emissions, and achieving green development; ③Level of external development (Wang and Wang, 2022). They were expressed as a share of GDP in terms of FDI. Some scholars argue that there is a "pollution halo", that foreign investment can compensate for capital deficiencies and contribute to the upgrading and transforming industrial structures, and that the spillover effects of technology and knowledge are also beneficial to green growth (Lin, 2022). It has also been argued that the preference of developed countries to shift highly polluting industries to developing countries has led to an increase in the proportion of foreign direct investment, which in turn has reduced the efficiency of green growth, i.e. the "pollution paradise" hypothesis (Wang et al., 2022). ④Research intensity (Shang et al., 2022). Expressed as internal expenditure on R&D in the district as a proportion of the district's GDP. R&D expenditure facilitates technological innovation and thus contributes to the efficiency of green growth. ⑤Human capital (Cao et al., 2022; Feng et al., 2022). Expressed in terms of the average number of years of education received locally. Human capital-rich regions have a better-qualified workforce and are more environmentally conscious, which can drive green growth efficiency. ⑥Level of financial development (Cao et al., 2022; Feng et al., 2022), expressed as a proportion of regional GDP of the balance of deposits and loans of financial institutions.

The regression of the inter-provincial panel data was conducted with the help of STATA 17.0 software. Before doing the sample regression analysis, the raw data of each variable was tested for multicollinearity and the results were a maximum VIF value of 5.28 and an average VIF of 2.72, both of which were <10, i.e. there was no multicollinearity. As fixed-effects Tobit models usually do not yield consistent and unbiased estimates, random-effects models work better. In this paper, a random effects panel Tobit model was used for regression analysis and the test results are shown in Table 7.

It can be seen that the impact of external factors on green growth efficiency differs significantly between the Yangtze River Economic Belt and the Yellow River Basin, specifically,

(1) The coefficient of the urbanization rate is significantly positive in both the Yellow River Basin and the Yangtze River Economic Belt, indicating that the urbanization process has a positive and significant impact on the green growth-efficiency values of the Yellow River Basin and the Yangtze River Economic Belt. This may be because urbanization has a greater pull on the development of urban–rural integration and economic output than the extent of pollution damage to the environment.

(2) The effect of environmental regulation on green growth efficiency is insignificant in both cases. The sign is positive in the Yangtze River Economic Belt and harmful in the Yellow River Basin. This indicates that environmental regulation does not lead to a significant increase in green growth efficiency. The possible reason for this is that the impact of environmental regulations on green development is long-term, and the construction of ecological civilization in the Yellow River Basin started late.

(3) The coefficient on the level of openness to foreign investment is not significant in the Yellow River Basin and passes the 5% significance test in the Yangtze River Economic Belt, both with negative signs. This indicates that while foreign direct investment brings in advanced production equipment and technology, it also creates a "pollution sanctuary" phenomenon, i.e. foreign polluting industries are transferred to developing countries with weaker environmental regulations with foreign investment, thus causing damage to the ecological environment.

(4) The impact of research intensity on green growth efficiency is not significant. This may be because China's technology R&D model has long been government-led and there is a disconnect between technology R&D and actual market demand, resulting in less efficient use of R&D funds. Secondly, due to the 'technology-environment' paradox, if technology is biased towards increasing the speed of production and achieving scale expansion, rather than towards green innovation, then technological advances will lead to increased production and increased pollutant emissions, to the detriment of ecological protection.

(5) The coefficient of human capital is insignificant in the Yangtze River Economic Belt and passes the 5% significance test in the Yellow River Basin, both with negative signs. This indicates that human capital has not yet played the role of a key factor in enhancing the efficiency of green growth, and the allocation of human capital is less efficient, thus inhibiting the innovation of green technology and the green development of the economy.

(6) The coefficient on the level of financial development was not

Table 7
Tobit model regression results analysis.

Variables and statistical parameters	Overall	Yellow River Basin	Yangtze River Economic Belt
Urbanization rate	0.023334***	0.0189293***	0.0220405***
Environmental regulation intensity	5.393625	−0.8623143	10.6491
Level of external opening	−6.82653***	−3.810844	−5.64229**
Research intensity	−0.04981	0.0145065	−0.1137659
Human Capital	−0.08905*	−0.1321837**	−0.0627313
Level of financial development	−0.08859**	−0.1098851**	−0.0161766
Constant term	1.111314***	1.705677***	0.7385719*

(Note: "***" indicates $p < 0.01$, "**" indicates $p < 0.05$, "*" indicates $p < 0.1$).

significant in the Yangtze River Economic Belt and passed the 5% significance test in the Yellow River Basin, both with negative signs. This is because capital is profit-seeking and a large amount of financial capital flows to capital-intensive enterprises, while the basic intensive enterprises are mainly secondary industries with high energy consumption and pollutant emissions, thus reducing the level of green growth. At the same time, commercial banks have monopolistic behavior, which affects the rational allocation of financial capital, reduces the liquidity of financial capital, and is not conducive to the spread and development of the green finance concept.

7. Conclusions and policy recommendations

7.1. Research conclusions

This paper selected relevant data from 2010 to 2020, measured and compared the green growth efficiency of the Yellow River Basin and the Yangtze River Economic Belt using a three-stage DEA model and the Malmquist Index, and established a panel Tobit model to identify the influencing factors of green growth efficiency. The main findings are as follows.

(1) It is necessary to exclude the influence of environmental factors on green growth efficiency. In general, the green growth efficiency of the 19 provinces (cities) in the two regions before and after the adjustment has changed relatively significantly, which proves that the green growth efficiency measurement using the three-stage DEA model is more objective and realistic. Excluding the external environmental factors such as economic, social, and institutional influences, and analyzing the green growth efficiency values of the two regions from the perspective of internal management, it is found that there is still much room for improvement in the green growth efficiency of many provinces and that the Yangtze River Economic Belt and the Yellow River Basin are mainly characterized by "high in the east and low in the west". By region, after excluding the influence of external environmental factors, the green growth efficiency values in the central part of the Yangtze River Economic Belt rose the fastest, followed by the western part, while the eastern part declined to a certain extent, and the eastern part of the Yellow River Basin also changed less. This indicates that there are differences in green growth efficiency within the Yangtze River Economic Belt and the Yellow River Basin and that the level of internal management in the east is higher than that in the west and the center.

(2) Secondly, a comparison of the Malmquist Index and its decomposition between the Yangtze River Economic Belt and the Yellow River Basin reveals that over the sample period, the Technological Progress Index declines overall in the Yangtze River Economic Belt and the Technical Efficiency Index plays a more significant role in green growth efficiency in the Yangtze River Economic Belt, while in the Yellow River Basin, technological progress plays a significant role in green economic growth.

(3) Finally, the Tobit model regression results show that the urbanization rate has a significant positive effect on both regions, while the effects of environmental regulation and research intensity are not significant. At the same time, the degree of influence of each factor is not the same in the Yangtze River Economic Belt and the Yellow River Basin. The regression results for the Yangtze River Economic Belt support the 'pollution sanctuary' hypothesis, while the results for the Yellow River Basin do not. The level of financial development and human capital has a significant effect on green growth efficiency in the Yellow River Basin, but not in the Yangtze River Basin.

7.2. Policy recommendations

Based on the findings of the study, this paper makes the following policy recommendations:

(1) Adhere to the concept of green development, and explore the path of efficiency improvement in line with regional characteristics. The two regions cannot take the old road of "pollution first and then treatment, resources, and environment for growth", and profoundly understand and resolutely implement the development policy of "grasping big protection and not big development", and take the road of "ecological priority and green development". high-quality development path.

(2) Both regions should promote industrial upgrading and urbanization as the main grasp, and choose a different focus. The Yangtze River Economic Zone should focus on controlling the scale of industries and actively use foreign investment to upgrade production technology to achieve clean production and reduce energy consumption. The Yellow River Basin should focus on governance, accelerating the upgrading of the industrial structure, adjusting the energy consumption structure, and strengthening investment in science and technology innovation.

(3) Take "leading the weak by the strong, gathering the points to become the surface" as the entry point to narrow the efficiency differences between and within regions. Based on the current problem of unbalanced and insufficient development, we will improve the synergistic development mechanism between the Yangtze River Economic Belt and Yellow River Basin in ecological governance, industrial collaboration, scientific and technological cooperation, and infrastructure interconnection, break through the inherent interest pattern and administrative barriers, and solve the problem of synergistic improvement of green growth efficiency with integrated thinking.

CRediT authorship contribution statement

Liang Liu: Resources, Supervision, Writing – review & editing. **Yirui Yang:** Conceptualization, Software, Writing – original draft. **Shu Liu:** Methodology, Software, Visualization. **Xiujuan Gong:** Conceptualization, Supervision. **Yuting Zhao:** Software, Methodology. **Ruifeng Jin:** Software, Investigation. **Hongyu Duan:** Software, Investigation. **Pan Jiang:** Project administration, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This study was jointly founded by the Sichuan Soft Science Research Program Projects: 2023JDR0278 & 2022JDR0177, and the National Natural Science Foundation of China: 72004188.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2023.110214.

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